Invasive Weed Optimization and its Features in Electromagnetics

Shaya Karimkashi, Student Member, IEEE, and Ahmed A. Kishk, Fellow, IEEE

Abstract—A new numerical stochastic optimization algorithm, inspired from colonizing weeds, is proposed for Electromagnetic applications. This algorithm, invasive weed optimization (IWO), is described and applied to different electromagnetic problems. The linear array antenna synthesis, the standard problem used by antenna engineers, is presented as an example for the application of the IWO. Compared to the PSO, The features of the IWO are shown. As another application, the design of aperiodic thinned array antennas by optimizing the number of elements and at the same time their positions is presented. By implementing this new scenario, thinned arrays with less number of elements and lower sidelobes, compared to the results achieved by genetic algorithm (GA) for the same aperture dimensions, are obtained. Finally, the IWO is applied to a U-slot patch antenna to have the desired dual-band characteristics.

Index Terms—Antenna arrays, aperiodic arrays, microstrip patch antenna, optimization method, thinned arrays.

I. INTRODUCTION

LECTROMAGNETIC designing problems usually involve several parameters which are non-linearly related to the objective functions. In order to solve these problems efficiently, evolutionary optimization algorithms have been considered and successfully applied to electromagnetic problems. Among these optimizers, genetic algorithm (GA) [1] and particle swarm optimization (PSO) [2] have received considerable attentions by the electromagnetic community due to their efficiency and simplicity [3]–[6]. In addition, other optimization methods including Ant Colony Optimizer (ACO) [7] and simulated annealing (SA) [8] have shown high capability of searching for global minimum in electromagnetic optimization problems [9]–[13].

Here, a new optimization algorithm, invasive weed optimization (IWO) and mainly some of its new features are introduced by illustrating its applications to various electromagnetic problems. This numerical stochastic optimization algorithm, inspired from weed colonization, was first introduced by Mehrabian and Lucus in 2006 [14]. It is shown that this optimizer not only in certain instances outperforms other

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The authors are with the Department of Electrical Engineering, University of Mississippi, University, MI 38677 USA (e-mail: skarimka@olemiss.edu; s.karimkashi@gmail.com; ahmed@olemiss.edu).

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optimizers like PSO, but also is capable of handling some new electromagnetic optimization problems.

The main purpose of this paper is to introduce the desirable attributes and new features of the IWO for Electromagnetic problems. Of course, the efficiency of this optimization method compared to the other optimizers depends on the problem and choosing control parameters. Below, we first represent the proposed IWO algorithm and its desirable features. Then, by conducting several array antenna synthesis problems, including linear and thinned array antennas, the efficiency and specific features of this new algorithm are shown. Finally, the method is employed in designing a U-slot microstrip patch antenna fed by an L-probe to have the desired reflection coefficient for dual-band applications.

II. IWO

A. The Inspiration Phenomenon

The IWO, inspired from the phenomenon of colonization of invasive weeds in nature, is based on weed biology and ecology. It has been shown that capturing the properties of the invasive weeds, leads to a powerful optimization algorithm. The behavior of weed colonization in a cropping field can be explained as follows:

Weeds invade a cropping system (field) by means of dispersal and occupy opportunity spaces between the crops. Each invading weed takes the unused resources in the field and grows to a flowering weed and produces new weeds, independently. The number of new weeds produced by each flowering weed depends on the fitness of that flowering weed in the colony. Those weeds that have better adoption to the environment and take more unused resources grow faster and produce more seeds. The new produced weeds are randomly spread over the field and grow to flowering weeds. This process continues till the maximum number of weeds is reached on the field due to the limited resources. Now, only those weeds with better fitness can survive and produce new weeds. This competitive contest between the weeds causes them to become well adapted and improved over the time.

B. Algorithm

Before considering the algorithm process, the new key terms used to describe this algorithm should be introduced. Table I shows some of these terms. Each individual or agent, a set containing a value of each optimization variable, is called a seed. Each seed grows to a flowering plant in the colony. The meaning of a plant is one individual or agent after evaluating its fitness.

| | Each individual in the colony | | |
|--------------------------|---|--|--|
| Agent/ Seed | containing a value of each optimization | | |
| | variable | | |
| Fitness | A value representing the goodness of | | |
| Titless | the solution for each seed | | |
| Plant | one agent/seed after evaluating its | | |
| Flant | fitness | | |
| Colony | The entire agents or seeds | | |
| Population Size | The number of plants in the colony | | |
| | The maximum number of plants | | |
| Maximum number of plants | allowed to produce new seeds in the | | |
| | colony | | |

TABLE I SOME OF THE KEY TERMS USED IN THE IWO

Therefore, growing a seed to a plant corresponds to evaluating an agent's fitness.

To simulate the colonizing behavior of weeds the following steps, pictorially shown in Fig. 1, are considered.

- First of all, the N parameters (variables) that need to be optimized should be selected. Then, for each of these variables in the N-dimensional solution space, a maximum and minimum value should be assigned (defining the solution space).
- 2. A finite number of seeds are being randomly dispread over the defined solution space. In other words, each seed takes a random position in the N-dimensional problem space. Each seed's position is an initial solution, containing N values for the N variables, of the optimization problem (initialize a population).
- 3. Each initial seed grows to a flowering plant. That is, the fitness function, defined to represent the goodness of the solution, returns a fitness value for each seed. After assigning the fitness value to the corresponding seed, it is called a plant (Evaluate the fitness of each individual).
- 4. Before the flowering plants produce new seeds, they are ranked based on their assigned fitness values. Then, each flowering plant is allowed to produce seeds depending on its ranking in the colony. In other words, the number of seeds each plant produces depends on its fitness value or ranking and increases from the minimum possible seeds production, S_{\min} , to its maximum, S_{\max} . Those seeds that solve the problem better correspond to the plants which are more adapted to the colony and consequently produce more seeds. This step adds an important property to the algorithm by allowing all of the plants to participate in the reproduction contest (Rank the population and reproduce new seeds).
- 5. The produced seeds in this step are being dispread over the search space by normally distributed random numbers with mean equal to the location of the producing plants and varying standard deviations. The standard deviation (SD) at the present time step can be expressed by

$$\sigma_{iter} = \frac{(iter_{\max} - iter)^n}{(iter_{\max})^n} \left(\sigma_{initial} - \sigma_{final}\right) + \sigma_{final}$$
(1)

where $iter_{max}$ is the maximum number of iterations. $\sigma_{initial}$ and σ_{final} are defined initial and final standard deviations, respectively and n is the nonlinear modulation index. Fig. 2 shows the standard deviation (SD) over the

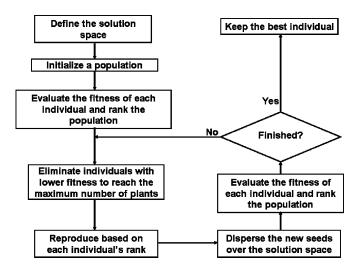


Fig. 1. Flow Chart showing the IWO algorithm.

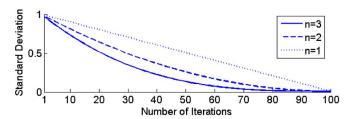


Fig. 2. Standard deviation over the course of the run.

course of a run with 100 iterations and different modulation indexes. It can be seen that the SD is reduced from the initial SD to the final SD with different velocities. The algorithm starts with such a high initial SD that the optimizer can explore through the whole solution space. By increasing the number of iterations, SD value is decreased gradually to search around the local minima or maxima to find the global optimal solution (dispersion).

- 6. After that all seeds have found their positions over the search area, the new seeds grow to the flowering plants and then, they are ranked together with their parents. Plants with lower ranking in the colony are eliminated to reach the maximum number of plants in the colony, P_{max} . It is obvious that the number of fitness evaluations, the population size, is more than the maximum number of plants in the colony (competitive exclusion).
- 7. Survived plants can produce new seeds based on their ranking in the colony. The process is repeated at step 3 till either the maximum number of iteration is reached or the fitness criterion is met (repeat).

C. Selection of Control Parameter Values

Among the parameters affect the convergence of the algorithm three parameters, the initial SD, $\sigma_{initial}$, the final SD, σ_{final} , and the nonlinear modulation index, n, should be tuned carefully in order to achieve the proper value of the SD in each iteration, according to (1). A high initial standard deviation should be chosen to allow the algorithm to explore the whole search area, aggressively. It seems that the IWO works well if the initial SD is set around a few percent (1 to 5 percent) of the

dynamic range of each variable. The final SD should be selected carefully to allow the optimizer to find the optimal solution as accurate as possible. A finer local optimum solution can be achieved by decreasing this parameter. However, it should be noticed that tuning the final SD much smaller than the precision criteria of the optimization variables, doesn't improve the final error level and may deteriorate the convergence rate of the optimization. Therefore, the final SD in each dimension should be selected based on the precision effect of that variable on the objective function. It was shown that the value of nonlinear modulation index has a considerable effect on the performance of IWO [14]. It was suggested that the best choice for n is 3. Besides (1), other functions to describe the standard deviation over the optimization process were considered. However, simulation results showed that (1) with n=3 is the best choice.

Maximum and minimum numbers of seeds are the two other important parameters needed to be selected. Based on different examples, it can be concluded that selecting the maximum number of seed between 3 and 5 leads to a good performance of the optimizer. Moreover, the minimum number of seeds is set to zero for all examples.

The maximum number of plants is another parameter that should be chosen in the IWO. Parametric studies show that increasing this parameter not necessarily increases the performance of the algorithm. It was found that the best performance can be achieved for many problems when the maximum number of plant is set between 10 and 20.

III. IWO FEATURES

One important property of the IWO is that it allows all of the agents or plants to participate in the reproduction process. Fitter plants produce more seeds than less fit plants, which tends to improve the convergence of the algorithm. Furthermore, it is possible that some of the plants with the lower fitness carry more useful information compared to the fitter plants. This algorithm, the IWO, gives a chance to the less fit plants to reproduce and if the seeds produced by them have good finesses in the colony, they can survive.

Another important feature of IWO is that weeds reproduce without mating. Each weed can produce new seeds, independently. This property adds a new attribute to the algorithm that each agent may have different number of variables during the optimization process. Thus, the number of variables can be chosen as one of the optimization parameters in this algorithm. Optimizing the number of variables gives such an interesting feature to the optimization that can handle some new electromagnetic design problems. The effectivity of this kind of optimization for designing aperiodic thinned array antennas is shown in Section V.

Finally, comparing some aspects of the IWO with two common and standard optimizers, GA and PSO, can clarify some features of this new algorithm. Provided that the number of iterations and the population size are considered as common requirements for all evolutionary algorithms, the initial and final standard deviation, nonlinear modulation index, and maximum and minimum number of seeds are the parameter of the IWO need to be tuned. In the GA, crossover and mutation rates

and in the PSO, inertial weight, W, cognitive rate, c_1 , social rate, c_2 , and the maximum velocity, $V_{\rm max}$, should be controlled to achieve the desired convergence. It has been shown that the choice of boundary conditions and also the maximum velocity are critical in convergence of the PSO algorithm [15]–[17]. Moreover, in the case of GA, both crossover and mutation rates affects the convergence of the problem [18]. The effect of these tuning parameters on the GA and PSO convergences are difficult to perceive, but by tuning the critical parameters in the IWO, the initial and final SD, a high-level control in the convergence and accuracy of the algorithm is achieved [19], [20]. In addition, the IWO shows a high stability with different boundary conditions.

IV. ARRAY ANTENNA DESIGN PROBLEMS

In this section, both the IWO and PSO are applied to the problem of synthesizing the far-field radiation patterns of linear array antennas. The consideration focuses on the optimizing of array antennas to achieve the desired radiation patterns given by user defined functions. For an array antenna with N elements, separated by a uniform distance d, the normalized array factor is given by

$$\mathbf{AF}(\theta) = \frac{1}{\mathbf{AF}_{\max}} \sum_{n=1}^{N} \mathbf{I}_n e^{\mathbf{j} 2\pi n \mathbf{d} \sin \theta / \lambda}.$$
 (2)

Where I_n are amplitude coefficients, θ is the angle from the normal to the array axis, and AF_{\max} is the maximum value of the magnitude of the array factor. d is assumed to be $\lambda/2$, where λ is the wavelength.

Comparisons are made between the performances of the IWO and the PSO in achieving desired radiation patterns. In the case of the IWO, restricted and invisible boundary conditions are two possible choices. The restricted boundary condition relocates the particle on the boundary that the particle hits. However, the invisible boundary condition allows a particle to stay outside the solution space while the fitness evaluation of that particle is skipped and a bad fitness value is assigned to that errant particle. For the case of the PSO, the boundary conditions including invisible (IBC), reflective (RBC), absorbing (ABC), damping (DBC), invisible/reflecting and invisible/damping are tested [16]. In addition, the velocity-clipping technique, showing good performance in the PSO, for different $V_{\rm max}$ values are implemented [9], [15].

The same number of population size and iterations are chosen for different algorithms. The population size is fixed to 40 for both algorithms. It should be noted that in the case of the IWO, the number of population is fixed by choosing the maximum number of plant population and also minimum and maximum number of seeds. In the coming examples, the maximum number of plants is fixed to 10 and the number of seeds increases linearly from 0 to 5. In the case of PSO, both the cognitive rate (c_1) and the social rate (c_2) are set to 2.0 and the inertial weight is varied linearly from 0.9 to 0.2 as suggested in [9], [17]. It should be also pointed out that various realizations of the same experiment produced results that are close to each other. All results reported are the average of 50 independent runs of the PSO or IWO algorithms and found to be sufficient.

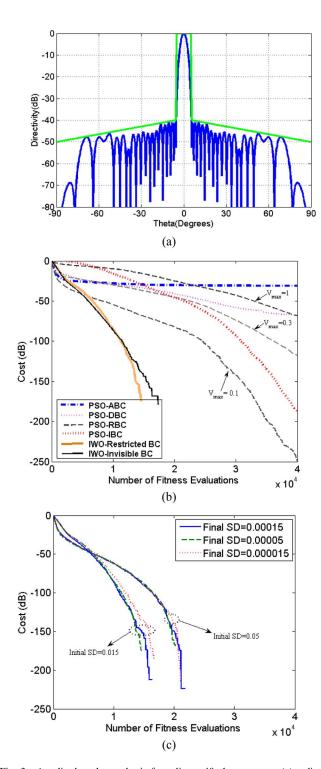


Fig. 3. Amplitude-only synthesis for a linear 40-element array (a) radiation pattern obtained using IWO, (b) convergence curves for the IWO and PSO with different boundary conditions. The maximum velocity limit is changed for the PSO, (c) convergence curves for the IWO with restricted boundary condition and different values of initial and final standard deviations.

A. Optimizing Sidelobe Patterns

In this section a linear 40-element array is considered to achieve the desired radiation pattern by optimizing the amplitude coefficients. The objective pattern is to obtain side lobe levels less than a tapered sidelobe mask that decreases linearly

TABLE II IWO PARAMETER VALUES FOR THE LINEAR 40-ELEMENT ARRAY OPTIMIZATION

| it _{max} | p_{max} | S _{max} | S _{min} | n | initial SD | final SD |
|-------------------|-----------|------------------|------------------|---|------------|----------|
| 1000 | 10 | 5 | 0 | 3 | 0.015 | 0.00005 |

TABLE III

COMPARISON OF AVERAGE NUMBER OF FITNESS EVALUATIONS REQUIRED PER
SUCCESSFUL RUN IN THE PSO AND THE IWO ALGORITHMS FOR THE LINEAR
40-ELEMENT ARRAY OPTIMIZATION

| Algorithm | Average number of fitness evaluations required per successful run |
|--------------------------|---|
| PSO-ABC | - |
| PSO-DBC | 162328 |
| PSO-RBC (Vmax = 1) | 92485 |
| PSO-RBC ($Vmax = 0.3$) | 62677 |
| PSO-RBC ($Vmax = 0.1$) | 42329 |
| PSO-IBC | 52496 |
| IWO-Restricted BC | 14692 |
| IWO-Invisible BC | 18212 |

from $-40~\mathrm{dB}$ to $-50~\mathrm{dB}$. The beamwidth of the array pattern is 11° and the number of sampling points is 359. It should be pointed out that "Don't exceed criterion" is utilized in the formulation of the objective function. That is, an error will be reported only if the obtained array factor exceeds the desired sidelobe levels.

Fig. 3(a) shows the desired and obtained radiation patterns achieved by the IWO. Since the desired envelope is symmetric, we exploit the symmetry of the current distribution. Thus, the number of optimization parameters reduces to the half of the array elements. The parameters used for the IWO are summarized in Table II. The performance of the IWO compared to the PSO for different boundary conditions is shown in Fig. 3(b). It can be seen that the performance of the PSO is dramatically changed by choosing either different boundary conditions or changing the maximum velocity. Moreover, the algorithm is trapped in a local minimum when the absorbing boundary condition is used while IWO achieves better performance for both invisible and restricted boundary conditions. The PSO algorithm tested by some other boundary conditions [16], [17] doesn't show any better performances. The average numbers of fitness evaluations required per successful run for both the IWO and PSO with different boundary conditions are shown in Table III. It can be seen that the IWO is faster than the PSO to achieve the same optimization goal for this problem. It should be mentioned that the 50 independent runs of the same experiment for each curve of the IWO algorithm are closer too each other compared to those for the PSO. These results are removed for brevity.

The performance of the IWO for different standard deviations is shown in Fig. 3(c). Different initial and final standard deviations are tried for IWO with the restricted boundary condition to evaluate the performance of this algorithm. It can be observed that by changing these parameters, the performance of the algorithm is slightly changed. Thus, by applying different boundary conditions or different standard deviation parameters, the IWO shows more stability compared to the PSO.

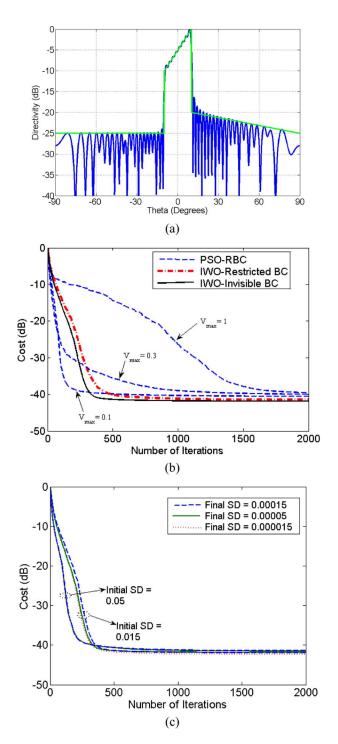


Fig. 4. Amplitude and phase synthesis for a linear 50-element array (a) radiation pattern obtained using IWO, (b) convergence curves for the IWO with different boundary conditions and PSO with reflective boundary condition (RBC) and different maximum velocity limit, (c) convergence curves for the IWO with invisible boundary condition and different number of initial and final standard deviations.

B. Shaped Beam Synthesis

The amplitude and phase optimization of a linear 50-element array antenna to achieve the desired radiation pattern is considered. Shaping the main beam requires minimizing the absolute difference between the desired and obtained radiation pattern. Meanwhile, the "Don't Exceed" criterion is considered in the

TABLE IV

COMPARISON OF AVERAGE NUMBER OF FITNESS EVALUATIONS REQUIRED PER
SUCCESSFUL RUN IN PSO AND IWO ALGORITHMS FOR THE LINEAR SHAPED
BEAM SYNTHESIS OPTIMIZATION

| | Average number of fitness evaluations required per successful run |
|--------------------------|---|
| PSO-RBC (Vmax = 1) | 130023 |
| PSO-RBC (Vmax = 0.3) | 88026 |
| PSO-RBC ($Vmax = 0.1$) | 28695 |
| IWO-Restricted BC | 19432 |
| IWO-Invisible BC | 13352 |

sidelobes region. Therefore, the objective is to obtain sidelobes levels less than the mask in the sidelobes region and main beam equal to the mask in the main beam region. The beamwidth of the array pattern is 20 degrees and the number of sampling points is 719.

The desired and obtained radiation patterns by using the IWO are shown in Fig. 4(a). The same optimization parameters, shown in Table II, are used for this synthesis problem, except the number of iterations which is set to 2000. The convergence curves for both the IWO with different boundary conditions and the PSO with reflective boundary condition (RBC) and different maximum velocities are shown in Fig. 4(b). It can be seen that the IWO convergence curves for both restricted and invisible boundary conditions converge to the same level. However, In the case of the PSO, by varying the maximum velocity limit, the performance of algorithm dramatically changes. Although in some cases the PSO is faster in convergence compared to the IWO, it traps in local minima. In addition, the 50 various realizations of the same experiment for each curve of the IWO algorithm are closer too each other compared to those for the PSO. Table IV shows the average numbers of fitness evaluations per successful run for both the IWO and PSO. The effect of varying the initial and final standard deviations on the convergence of the IWO with invisible boundary condition is shown in Fig. 4(c). It can be seen that by varying the initial SD, the convergence rate of the algorithm is improved and compete with the results obtained by PSO in the first number of iterations. However, neither the initial nor the final SD has any critical effect on the final error level. The IWO appears to be more stable since by applying different boundary conditions or different initial or final standard deviation values, the convergence speed or the level of the cost function doesn't change too much. Therefore, the IWO doesn't need much effort on tuning the parameters.

V. THINNED ARRAY ANTENNA

In this section, thinned planar array antennas are considered as the next optimization problem to show the effectivity and some special features of the IWO. By some modifications in the IWO, the number of elements and the position of those elements can be optimized which results in a new scenario for developing thinned arrays. By applying this scenario, planar thinned arrays with less number of elements and higher efficiencies are obtained.

Thinned arrays, generally produced by removing certain elements from a fully populated half wavelength spaced array, are

usually designed to generate low sidelobe levels. Different optimization algorithms including GA, PSO, Simulated Annealing and Ant Colony have been applied to remove the elements in such a way to have the lowest possible sidelobe levels [19]–[26]. Although, the thinned arrays obtained by using these algorithms produce low sidelobes levels, it has been shown that by considering the aperiodic arrangements, lower sidelobes levels can be achieved. This can be done by optimizing the inter-element spacing of periodic arrays or already thinned arrays to have lower sidelobes levels [20], [21], [27]–[30].

In this section, by some modifications in the IWO, the number of elements and at the same time their locations, the inter-element spacing, are optimized. It is shown that by using this algorithm, capable of optimizing such a problem, lower sidelobes levels with less number of elements can be achieved. Fewer elements for a given aperture mean reducing the cost and weight of the antenna system. It should be pointed out that the array is uniformly excited (all elements have identical current amplitude and phase). The advantage of uniform amplitude excitation is clear from the point of view of the feed network.

A. Modified IWO

As it was mentioned in Section II, in the IWO, each weed (agent) may have different number of variables during the optimization process. By taking this feature of the algorithm, different number of variables for each agent can be considered during the optimization. This modified IWO works similar to the routine explained in Section II, some modifications, however, should be made in the algorithm process to take the number of elements as an optimization parameter.

In this modified version of the IWO, each agent, corresponding to an array antenna, has different number of elements. Thus, the fitness value of each agent is calculated based on the number of elements and the position of each element in that agent. Similar to the general IWO algorithm, each flowering plant produces new seeds based on its ranking in the colony. That is, the new arrays appear in the colony. However, the reproduction process is modified to have different number of elements for each produced array antenna. In the reproduction process, each element in the array is removed and then reproduces some new elements in that array. The number of new elements produced by each old element is defined to be a constant value in each iteration. Then, these new elements are being dispread over the aperture by normally distributed random numbers with mean equal to the location of the producing element and varying standard deviations. The standard deviation (SD) is defined similar to (1) where it starts from a large value, called initial SD, and by increasing the number of iterations; decreases gradually to a small value, called final SD.

Without any limitations on the reproduced elements, the number of elements increases dramatically. Moreover, the distance between elements should be controlled not to have elements very close to each other. In order to overcome these problems, each new produced element is allowed to be located on the aperture if it is not closer than a predefined value (usually half wavelength or the size of the antenna element of the array) to any of the other elements already located on the aperture.

By choosing a relatively large value for the initial SD, the new elements are dispread over the aperture and the possibility of different number of elements over the aperture are tested. Then, by decreasing the SD to a small value, the position of each element on the aperture is optimized. Therefore, the number of elements and the location of each element are optimized.

It should be noted that in this modified version of IWO the whole process explained in Section II is carried out. Meanwhile, the modified reproduction process is taken into account for each agent.

B. Planar Thinned Array Examples

As the first design problem of thinned arrays, a rectangular planar array with the aperture of $9.5\lambda \times 4.5\lambda$ is considered. The objective is to minimize the maximum SLL in the $\varphi=0^\circ$ and $\varphi = 90^{\circ}$ planes. This problem is selected to compare the obtained result with the results in [19] and [28]. In [19] a 20×10 element planar array with a half a wavelength distance between uniformly spaced elements was thinned using GA by turning off some elements in that aperture. The optimal solution is a thinned array with 108 turned on elements on the rectangular aperture [19, Fig. 7]. The optimized SLLs are equal to -20.07 dB in $\varphi = 0^{\circ}$ plane and $-19.76 \, \mathrm{dB}$ in $\varphi = 90^{\circ}$ plane [19, Fig. 9]. The fitness value of the optimal solution, defined as the sum of maximum SLLs in both planes, is -39.83 dB. The same problem is considered in [28] by optimizing the inter-element spacing between 108 elements of the obtained thinned array in [19], using a modified real GA to achieve lower SLLs. The optimal solution [28, Fig. 6] shows a lower fitness value, -45.456 dB, and SLLs equal to $-29.597 \, \mathrm{dB}$ and $-15.859 \, \mathrm{dB}$ in $\varphi = 0^{\circ}$ and $\varphi = 90^{\circ}$, respectively [28, Fig. 5].

In order to optimize this problem by using the IWO and based on the described method, the number of elements and their positions are optimized to obtain the lowest SLLs at the desired planes. The normalized array factor of a planar array with N elements is given by

$$AF(\theta) = \frac{1}{AF_{\text{max}}} \times \sum_{n=1}^{N} I_n \left(\frac{\exp j2\pi (Lx_n \sin \theta \cos \varphi + Ly_n \sin \theta \sin \varphi)}{\lambda} \right) (3)$$

where Lx_n and Ly_n are the locations of elements in x and y direction, respectively. This equation assumes that the array lies in the x-y plane. Since the desired pattern is symmetric about the x-axis and y-axis, a quarter of the aperture is considered to reduce the number of optimization parameters to the quarter of the array elements. The minimum distance between elements is assumed to be half wavelength. It should be noted that the amplitude coefficients, I_n , are assumed to be 1.

Set up of the IWO algorithm for solving this problem is summarized in Table V. The final SD is chosen to be a small value to optimize the location of each element with a high precision. An averaging of five runs is considered and found to be sufficient. The best thinned array obtained is presented in Table VI. Fig. 5(a) shows the radiation patterns of the obtained thinned array in both $\varphi=0^\circ$ and $\varphi=90^\circ$ planes. The fitness value, the sum of maximum SLLs in both planes, is $-65.40~\mathrm{dB}$ and the

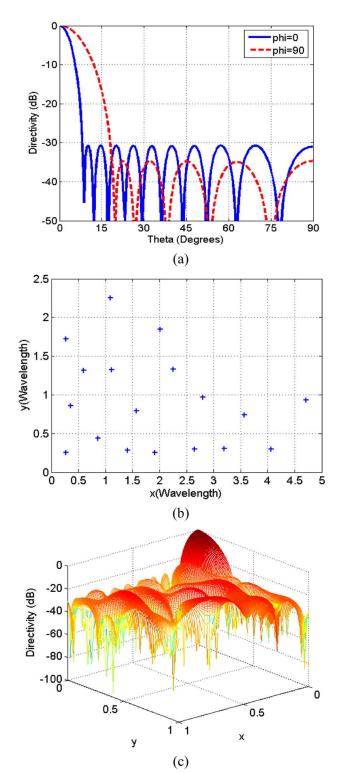


Fig. 5. Optimized thinned array antenna for reduction of SLL in the $\varphi=0^\circ$ and $\varphi=90^\circ$ planes, (a) radiation patterns in the $\varphi=0^\circ$ and $\varphi=90^\circ$, (b) the array configuration of the optimized thinned array, (c) 3D radiation pattern.

obtained SLLs are $-34.72~\mathrm{dB}$ in $\varphi=0^\circ$ plane and $-30.68~\mathrm{dB}$ in $\varphi=90^\circ$ plane. The array configuration of the thinned array for the upper right quarter of the aperture is depicted in Fig. 5(b) (compare with [28, Fig. 6] and [19, Fig. 7]). 18 elements (72 elements for the whole aperture) are the optimized number of elements to achieve the lowest SLLs. Comparing these results with those in [19] and [28] it can be concluded that by employing this

 $\label{thm:table v} TABLE\ V$ IWO Parameters for the Thinned Array Optimization Problems

| it _{max} | p _{max} | S _{max} | S _{min} | n | initial SD | final SD |
|-------------------|------------------|------------------|------------------|---|------------|----------|
| 500 | 55 | 5 | 0 | 3 | 0.25λ | 0.0005λ |

TABLE VI THE COORDINATES OF THE ARRAY ELEMENTS IN WAVELENGTH: $i(x_i,y_i)$

| 1(0.264,1.720) | 2(0.269,0.254) | 3(0.354,0.860) | 4(0.593,1.314) |
|-----------------|-----------------|-----------------|-----------------|
| 5(0.864,0.435) | 6(1.093,2.250) | 7(1.111,1.324) | 8(1.413,0.283) |
| 9(1.576,0.789) | 10(1.913,0.253) | 11(2.014,1.845) | 12(2.249,1.331) |
| 13(2.644,0.301) | 14(2.796,0.969) | 15(3.192,0.306) | 16(3.568,0.742) |
| 17(4.061,0.295) | 18(4.708,0.935) | | |

TABLE VII THE COORDINATES OF THE ARRAY ELEMENTS IN WAVELENGTH: $i(x_i,y_i)$

| 1(0.271,0.186) | 2(0.289, 0.254) | 3(0.292,0.763) | 4(0.537,1.250) |
|-----------------|------------------|-----------------|-----------------|
| 5(0.855, 0.258) | 6(0.907, 0.785) | 7(1.103,2.023) | 8(1.184,1.269) |
| 9(1.530, 0.893) | 10(1.672,0.257) | 11(1.772,2.234) | 12(2.174,0.315) |
| 13(2.241,1.112) | 14(2.669, 0.399) | 15(2.944,1.433) | 16(3.188,0.846) |
| 17(3.568,1.535) | 18(4.053,0.318) | 19(4.701,0.421) | 20(4.712,1.691) |

algorithm, much lower SLLs at both planes are achieved with more than 25% saving on the number of elements.

Another optimization problem is the reduction of SLLs in all φ planes. It can be seen from Fig. 5(b) that most of the elements are around the x and y axes. Such an array configuration produces high SLLs at some other planes as shown in Fig. 5(c). In order to reduce the SLLs in all the φ planes, we decided to define the fitness function as the maximum SLL in $\varphi = 0^{\circ}$, $\varphi = 45^{\circ}$ and $\varphi = 90^{\circ}$ planes to have more elements at the central part of the aperture. This fitness function helps to have less computation and avoid an expensive optimization process. The same optimization parameters shown in Table V are chosen for this problem. Table VII represents the obtained thinned array configuration. The array radiation pattern cuts in $\varphi = 0^{\circ}$, $\varphi = 45^{\circ}$ and $\varphi = 90^{\circ}$ for the best optimal solution are shown in Fig. 6(a). The array configuration, shown in Fig. 6(b), consists of 80 elements (for the whole aperture) distributed on the aperture. It is observed that more elements are located at the central part of the aperture as it was expected. Fig. 6(c) is the 3D radiation pattern of this array. Though low SLLs are obtained at the three cuts shown in Fig. 6(a), SLLs haven't decreased effectively in the other φ planes.

In order to have low SLLs in all planes, the fitness function is defined as the maximum SLLs in all the φ planes. The same optimization parameters are selected for this problem. The result of optimization is a thinned planar array with 92 elements (for the whole aperture) depicted in Table VIII. Fig. 7(a) shows the array configuration on a quarter of the aperture. The radiation pattern of this array is shown in Fig. 7(b) where the maximum SLL is $-21.2~\mathrm{dB}$. comparing this results to that of [28], where GA is used to minimize the SLLs for 100 elements sparse array [28, Figs. 7 and 8], one can see that the IWO results lower SLL ($-18.84~\mathrm{dB}$ in [28]) with less number of elements.

VI. DUAL-BAND U-SLOT PATCH ANTENNA

To demonstrate the applicability of the IWO in electromagnetics, the design of a U-slot patch antenna [31], [32] to have the desired dual-band characteristics is considered. This concept

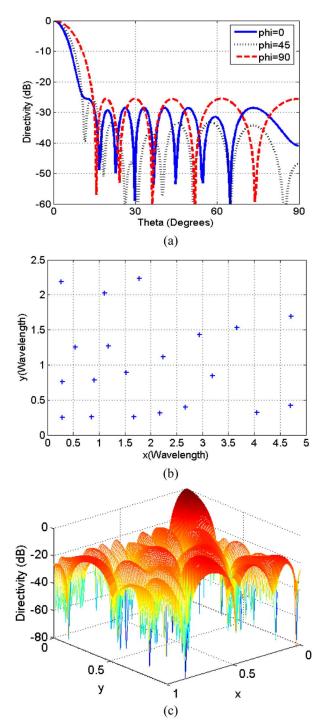


Fig. 6. Optimized thinned array antenna for reduction of SLL in the $\varphi=0^\circ$, $\varphi=45^\circ$ and $\varphi=90^\circ$ planes, (a) radiation patterns in the $\varphi=0^\circ$, $\varphi=45^\circ$ and $\varphi=90^\circ$, (b) the array configuration of the optimized thinned array, (c) 3D radiation pattern.

was introduced in [33], [34] where a U-slot in the patch fed by an L-probe produces notches within the matching band. Fig. 8 shows the configuration of the antenna structure. The L-probe feeding technique is used to have a wideband patch antenna [35], [36] and then the U-slot is cut on the patch to introduce notches, resulting in dual-band operation. The length (L) and the width (W) of the patch and also the position (P_f) and height of L-probe (H_L) are predefined. Then, the optimization of seven other parameters, H, L_L , U_a , U_b , U_d , U_x and U_b are required.

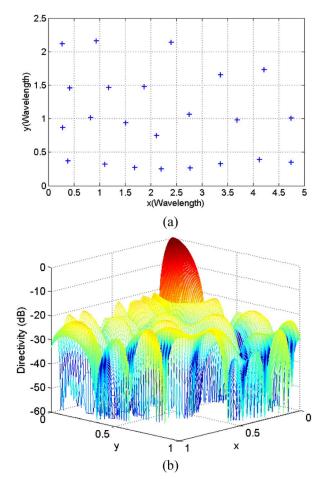


Fig. 7. Optimized thinned array antenna for reduction of SLL in all φ planes, (a) The array configuration of the optimized thinned array, (b) 3D radiation pattern.

TABLE VIII THE COORDINATES OF THE ARRAY ELEMENTS IN WAVELENGTH: $i(x_i,y_i)$

| 1(0.271,2.119) | 2(0.285,0.866) | 3(0.385,0.369) | 4(0.425,1.457) |
|-----------------|-----------------|-----------------|-----------------|
| 5(0.832,1.015) | 6(0.940,2.159) | 7(1.106,0.316) | 8(1.182,1.465) |
| 9(1.511,0.936) | 10(1.688,0.273) | 11(1.878,1.475) | 12(2.118,0.750) |
| 13(2.213,0.251) | 14(2.398,2.139) | 15(2.770,0.266) | 16(2.751,1.061) |
| 17(3.363,0.327) | 18(3.367,1.655) | 19(3.690,0.979) | 20(4.127,0.393) |
| 21(4.218,1.734) | 22(4.750,0.350) | 23(4.750,1.007) | |

Since these parameters are not independent, their ranges should be chosen carefully.

The purpose of the optimization is to achieve the desired reflection coefficient within the matching band, 2–4 GHz. The IWO is linked to a MoM program that simulates the antenna reflection coefficient at 20 points within the frequency range. The fitness function is defined as the summation of differences between the relative values of the desired and obtained reflection coefficient at all 20 frequencies. The objective is to have –12 dB reflection coefficient at 2.4 GHz and 3.3 GHz frequencies and zero at the other frequencies. The reason for choosing –12 dB as the desired reflection coefficient is that decreasing this value results in a very low value in one frequency but relatively high at the other one.

The restricted boundary condition is applied to this optimization problem. The maximum number of plant population is selected to be 10 and the number of seeds is varied linearly from

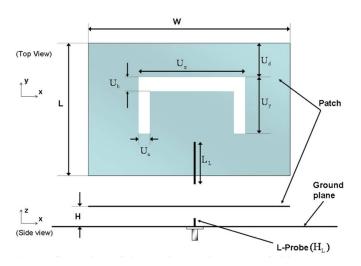


Fig. 8. The configuration of the U-slot patch antenna fed by an L-probe with top view (top) and side view (lower).

TABLE IX
FINAL DIMENSIONS OF THE OBTAINED U-SLOT PATCH ANTENNA IN MM

| | W | L | | H* | | H_{L} | L _L * | | Ua* |
|--|------|-----|------------------|--------|------------------|---------|------------------|------------------|-----|
| | 44.5 | 36. | 4 | | | 7.0 | 15.94 | 15.941 | |
| | | | U _d * | | U _x * | U, | * | P_{f} | |
| | | | 9.333 | 14.525 | | 21.799 | | 1.0 | |

Optimized parameter

4 to zero. The nonlinear modulation index is set to 3 over 100 iterations.

The optimized parameters of the U-slot patch antenna are shown in Table IX. After simulating the antenna with more number of frequencies within the frequency range, the reflection coefficient shown in Fig. 9(a) is achieved. Fig. 9(b) illustrates the convergence curve of IWO algorithm which is the normalized curve of the fitness function in dB. It can be seen that the desired reflection coefficient within the frequency range of the U-slot antenna is achieved.

VII. CONCLUSION

A numerical stochastic optimization algorithm based on the weed ecology was introduced for electromagnetic applications. The IWO algorithm is capturing the properties of the invasive weeds, which led to a powerful optimization algorithm. By applying the IWO to the array antenna synthesis problems, the performance of this algorithm was investigated. It was shown that in certain instances the IWO outperforms the PSO in the convergence rate as well as the final error level. Moreover, the performance of the IWO for different boundary conditions and tuning parameters was evaluated. From the simulation results, it was observed that this algorithm is very stable and efficient against different parameter values. The IWO was also utilized to design aperiodic planar thinned array antennas by optimizing the number of elements and at the same time their positions. It was shown that by using this technique, thinned arrays with less number of elements and lower sidelobes levels, compared to

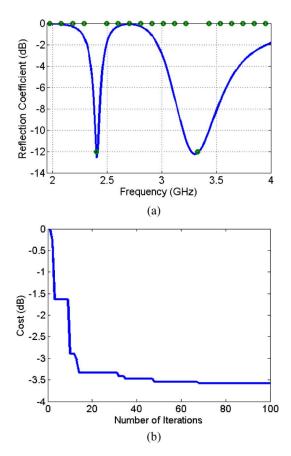


Fig. 9. U-slot patch antenna fed by an L-probe (a) the obtained reflection coefficient, and (b) the convergence curve.

the results already achieved from other methods were obtained. Also, the IWO was applied to the design of a U-slot patch antenna fed by an L-probe to have a dual band performance with the desired reflection coefficient.

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Shaya Karimkashi was born in Tehran, Iran. in 1980. He received the B.S. degree in electrical engineering from K. N. Toosi University of technology, Tehran, and the M.S. degree in electrical engineering from University of Tehran, in 2003 and 2006, respectively. Currently he is working toward Ph.D. degree at the University of Mississippi, University.

His research interests include array antennas, focused antennas, reflector antennas, optimization methods in EM and microwave measurement techniques.



Ahmed A. Kishk received the B.S. degree in electronic and communication engineering from Cairo University, Cairo, Egypt, in 1977, and the B.S. degree in applied mathematics from Ain-Shams University, Cairo, Egypt, in 1980, and the M.Eng and Ph.D. degrees from the University of Manitoba, Winnipeg, Canada, in 1983 and 1986, respectively.

From 1977 to 1981, he was a Research Assistant and an Instructor at the Faculty of Engineering, Cairo University. From 1981 to 1985, he was a Research Assistant in the Department of Electrical

Engineering, University of Manitoba, where, rom December 1985 to August 1986, he was a Research Associate Fellow. In 1986, he joined the Department of Electrical Engineering, University of Mississippi, as an Assistant Professor. He was on sabbatical leave at Chalmers University of Technology, Sweden during the 1994–1995 academic years. He is now a Professor at the University of Mississippi (since 1995). His research interest includes the areas of design of millimeter frequency antennas, feeds for parabolic reflectors, dielectric resonator antennas, microstrip antennas, EBG, artificial magnetic conductors, soft and hard surfaces, phased array antennas, and computer aided design for antennas. He has published over 200 refereed journal articles and 27 book chapters. He is a coauthor of the book *Microwave Horns and Feeds* (London, U.K., 1994; New York: 1994) and a coauthor of chapter 2 in *Handbook of Microstrip Antennas* (London, U.K., 1989).

Dr. Kishk received the 1995 and 2006 outstanding paper awards for papers published in the Applied Computational Electromagnetic Society Journal. He received the 1997 Outstanding Engineering Educator Award from Memphis section of the IEEE. He received the Outstanding Engineering Faculty Member of the Year in 1998 and 2009, Faculty Research Award for outstanding performance in research on 2001 and 2005. He received the Award of Distinguished Technical Communication for his paper published in the IEEE Antennas and Propagation Magazine, 2001. He also received The Valued Contribution Award for outstanding Invited Presentation, "EM Modeling of Surfaces with STOP or GO Characteristics-Artificial Magnetic Conductors and Soft and Hard Surfaces" from the Applied Computational Electromagnetic Society. He received the Microwave Theory and Techniques Society Microwave Prize 2004. He is a Fellow member of IEEE since 1998 (Antennas and Propagation Society and Microwave Theory and Techniques), a member of Sigma Xi society, a member of the U.S. National Committee of International Union of Radio Science (URSI) Commission B, a member of the Applied Computational Electromagnetics Society, a Fellow member of the Electromagnetic Academy, and a member of Phi Kappa Phi Society. He was an Associate Editor of the IEEE Antennas and Propagation Magazine from 1990 to 1993 and is now an Editor. He was a Co-editor of the Special Issue on Advances in the Application of the Method of Moments to Electromagnetic Scattering Problems in the ACES Journal, was an Editor the during 1997, and was Editor-in-Chief from 1998 to 2001. He was the Chair of Physics and Engineering Division of the Mississippi Academy of Science (2001-2002). He was a Guest Editor of the Special Issue on Artificial Magnetic Conductors, Soft/Hard Surfaces, and Other Complex Surfaces of the IEEE TRANSACTIONS ON ANTENNAS AND PROPAGATION, January 2005.